



Search for Neutrinoless Double-Beta Decay with KamLAND-Zen Applying Advanced Spallation Background Reduction

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博士学位論文内容の要旨
及び
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論文内容要旨

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氏 名	林田 眞悟	提出年	平成 30 年
学位論文の 題 目	Search for Neutrinoless Double-Beta Decay with KamLAND-Zen Applying Advanced Spallation Background Reduction (先進的な核破砕由来背景事象低減を適用した KamLAND-Zen におけるニュー トリノを伴わない二重ベータ崩壊の探索)		

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The discovery of neutrino oscillation revealed the existence of extremely light neutrinos. Mass acquisition mechanism of neutrinos cannot be explained by Standard Model. However, assuming that the neutrinos have a Majorana property, the fact that the neutrinos naturally acquire an extremely light mass can be explained by the See-saw mechanism. The only realistic method to verify Majorana property at this point, is neutrino-less double beta decay observation. Double beta decay is a phenomenon which two beta decays occur in one nucleus at the same time, emitting two electrons and two neutrinos ($2\nu\beta\beta$). This decay is allowed by the standard theory. If neutrinos have Majorana property, double beta decay without emitting any neutrinos occur ($0\nu\beta\beta$). Currently, various experiments around the world are searching for $0\nu\beta\beta$ decay, however it has not been observed yet. Only the lower limit of decay half-life is obtained.

KamLAND-Zen is an experiment searching for $0\nu\beta\beta$ decay using ^{136}Xe as the double beta decay nucleus, and the half-life limit $> 1.07 \times 10^{26}$ yr (90% C.L.) was obtained. In this experiment, one of the dominant background events is the ^{10}C decay which is a spallation product induced by the cosmic-ray muon. ^{10}C background reduction is very important for further investigation of $0\nu\beta\beta$.

In this research, newly developed neural networks method for the particle identification is applied to KamLAND-Zen data to reduce the ^{10}C background further. The neural networks learn the particle identification by processing a large amount of training samples. Author optimized KamLAND-Zen Monte Carlo (KamLAND-Zen MC) to reproduce real data within 5% accuracy. A large amount of training samples is generated by the KamLAND-Zen MC to implement into the neural networks method.

The neural networks were designed to classify the events into three categories such as ^{10}C -oPs, ^{10}C -pPs and $\beta\beta$. The first two types of events are ^{10}C decay backgrounds that should be distinguished from $\beta\beta$ type events which is a "signal". It is successfully obtained that the developed neural networks method has the ^{10}C background reduction efficiency of $(55 \pm 7.3)\%$ with signal inefficiency of $(20 \pm 2.4)\%$.

The developed neural networks method was applied to the data of a part of volume region in Period-2 where the background event was small in KamLAND-Zen, and the result of $0\nu\beta\beta$ decay half-life $> 6.8 \times 10^{25}$ yr (90% C.L.) is obtained. By combining with the results of other KamLAND-Zen periods, the $0\nu\beta\beta$ decay half-life improved to $> 1.12 \times 10^{26}$ yr. This half-life limit corresponds to the effective Majorana neutrino mass limit $< (60-161)$ meV (90% C.L.), where the range comes from by the uncertainty of the nuclear model. This result is the best limit among $0\nu\beta\beta$ search experiments, and it is reaching near the inverted mass hierarchy region.

This research shows that neural networks method has a potential to be a powerful method to reduce the ^{10}C background. Further improvement is expected by applying neural networks method to the whole volume and the whole period. Furthermore, neural networks method is expected to show its power in the next phase of KamLAND-Zen (KamLAND-Zen 800 or KamLAND2-Zen) which is aiming at verifying the Majorana property of neutrinos in the inverted hierarchy region.

The particle identification method, which developed in this research, has brought about extremely important techniques for the future KamLAND-Zen experiment.

論文審査の結果の要旨

本論文は、二重 β 崩壊核 ^{136}Xe におけるニュートリノを伴わない二重 β 崩壊 ($0\nu2\beta$) を探索するカムランド禅実験において、ニューラルネットワークを使った解析によって宇宙線原子核破碎起源のバックグラウンドを低減し、ニュートリノ質量の準縮退構造ほぼ全域においてニュートリノのマヨラナ性を検証するものである。

カムランド禅実験は、ニュートリノ検出器カムランド中心に ^{136}Xe 含有液体シンチレータをミニバルーンに内包して導入し、高感度で $0\nu2\beta$ を探索する。蒸留純化後の主要バックグラウンドのうち宇宙線原子核破碎起源の ^{10}C は γ 線を伴う β +崩壊で発光点が広がる特徴を持つ。さらに陽電子は、ポジトロニウムを形成して時間分布を広げる。本論文では、ニューラルネットワークを使い時間分布の広い事象を排除する汎用的手法を開発した。ニューラルネットワークを使った解析では適切な学習データと、よく理解できた実事象での性能検証・較正が重要である。緻密に最適化した大量のシミュレーションデータで学習したニューラルネットワークを使い、 $0\nu2\beta$ の除去率を $20 \pm 2.4\%$ に抑えたまま ^{10}C を $55 \pm 7.3\%$ 除去することに成功している。また、 ^{60}Co 較正線源、 ^{214}Bi - ^{214}Po 遅延同時計測で識別した ^{214}Bi 、ニュートリノを伴う二重ベータ崩壊、 ^{208}Tl を、それぞれ検証用の高純度実データとし、 $0\nu2\beta$ 領域を含む広いエネルギー領域・ β 線 γ 線の異なる割合を含めてニューラルネットワークの実データでの振る舞いを検証し、除去効率および系統誤差を算出した。この解析は、純化後後半のデータで $0\nu2\beta$ の半減期に対して約 15% 厳しい制限を与えており、純化前後全てのデータを使った解析では、 $0\nu2\beta$ の半減期に対して 1.12×10^{26} 年以上 (90%信頼度) の制限を与える。マヨラナ有効質量換算で 60-161 meV 以下の制限に相当し、世界で最も厳しい制限であるとともに、準縮退構造ほぼ全域でマヨラナ性を否定することに成功している。この手法は γ 線を伴うバックグラウンド全般の排除に有効で、特に将来計画の感度向上に大きく貢献する。

本論文は、世界最大量の二重 β 崩壊原子核の観測データから、世界で最も厳しいニュートリノのマヨラナ有効質量に対する制限を与え、将来の高感度探索でも有効な汎用性の高いバックグラウンド低減の解析手法を提示したものである。これらの成果は、自立して研究活動を行うのに必要な高度な研究能力と学識を有することを示しており、したがって、林田眞悟提出の博士論文は博士 (理学) の学位論文として合格と認める。